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Developing A Novel Modeling Framework for Residential Home's Occupant Behaviors in Support of Building-to-Grid Integration Research

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Abstract

Building-to-grid (B2G) integration research aims to use buildings as flexible power demand resources to provide grid services. Occupant behaviors in residential homes, one of the major building types, significantly influence power demands. This paper develops a novel modeling framework for residential homes' occupant behaviors supporting B2G integration research. This high-fidelity modeling framework is built based on well-accepted models and controls. In addition, the proposed framework provides an interface to connect standardized power system tools with building models. It has the flexibility of scaling up models and controls from a single building to communities and urban districts.

Introduction

Building-to-grid (B2G) integration research aims to use buildings as flexible power demand resources to provide grid services (Neukomm, Nubbe, and Fares 2019). As major energy consumers, buildings accounted for approximately 39% of energy consumption (EIA 2022a) and 35% of energy-related CO_2 emissions (EIA 2022b) in the United States (U.S.) in 2021. Buildings have significant power optimization potential that can benefit power system operations. For example, previous research (Huang et al. 2021) showed that the aggregated power flexibility for all commercial buildings in the U.S. can be approximately 80 GW in the afternoon on a summer day by only providing ± 1.11 °C indoor air temperature set point flexibility.

As one of the major building types, residential homes play a substantial role in energy saving and power demand optimizations (Hu and Xiao 2020). Occupant behaviors in residential homes significantly influence power demands. Residents interact directly with various operational aspects, including heating, ventilation, air-conditioning (HVAC) systems, and electrical devices. These interactions, involving control adjustments and regular use, significantly impact electricity consumption and load profiles.

Occupant-related operations in buildings can be classified into two categories. The first category is occupant-based controls (Ye et al. 2021). Occupancy sensors monitor the presence or number of occupants in a space. The actuators in controllers operate the systems, such as lighting, air conditioning, and ventilation. Common data sources for presence models include occupancy, CO_2, wireless camera sensor data, time-use data, light switching data, etc. (Yan and Hong 2018b; Erickson et al. 2009; Yan et al. 2017; Richardson, Thomson, and Infield 2008). The second category is manual operation probability (Eilers, Reed, and Works 1996). The operation actions contain uncertainties from occupants' preferences (Wang 2021; Wang et al. 2021). Occupant behavior prediction is a complicated stochastic mechanism and can be influenced by multiple contextual factors (Yan et al. 2015; Warren and Parkins 1984).

Building occupant behavior modeling consists of two major parts (Wang 2021; Wang et al. 2021; Yan and Hong 2018a): (1) Occupant presence/movement modeling that describes whether the occupants are in a building and where they are. (2) Occupant behavior (i.e., action) modeling that describes occupants' interactions with building energy systems. For the first part, stochastic models, developed by survey data, in-situ data, etc., are popular to describe occupant presence/movement (Wilke et al. 2013; Chen, Hong, and Luo 2018). For example, the first-order Markov chain technique has been widely adopted in developing occupancy models (Erickson et al. 2009; Page et al. 2008; Dong et al. 2010; Andersen et al. 2014). However, accurately describing and modeling occupant behaviors is difficult, especially in residential homes since more interactions happen based on occupants' preferences (Langevin, Wen, and Gurian 2013). One existing paper (O'Brien and Gunay 2014) summarized the contextual factors for occupant-related controls, including availability and accessibility of personal control, complexity and transparency of automation systems, presence of mechanical/electrical systems providing alternative means of comfort, view and connection to the outdoors, interior design, experiences and foreseeable future conditions, visibility of energy use, and personal factors, such as occupancy patterns and social constraints, culture, age, and gender. Designing a deterministic occupant behavior model and related operations in a residential home is complex. The inherent uncertainty tied to occupant behavior often results in disparities between simulated and actual building energy consumption (Clevenger and Haymaker 2006). A quasi-dynamic interoperability framework for residential homes is lacking, which can accurately predict occupant behaviors and related operations.

To address the research gap, this paper develops a novel modeling framework for residential homes' occupant behaviors supporting B2G integration research. This modeling framework has three highlights: (1) The occupant behavior models and related operations in this modeling framework are high fidelity. (2) It has an interface to power system tools. (3) It allows scaling up to large-scale research. The rest of the paper is organized as follows: Section 2 introduces the prototype residential buildings used as the starting point for the occupant behavior models. Section 3 describes the system modeling for occupant behavior models and related operations. Section 4 provides a case study to demonstrate the work for this modeling framework. Section 5 summarizes this research and plan.

Prototype Residential Homes

The Pacific Northwest National Laboratory developed a set of prototypical building models, called DOE Prototype Building Models, to support technical analyses for published model codes and potential changes (DOE and PNNL 2023b). This paper leverages the DOE Residential Prototype Building Models to study occupant behaviors and related controls. Table 1 summarizes the specifications of these models.

Figure 1 displays the current weekday schedules in a prototype residential signal-family home. There are three residents in this home. During the daytime, some of them do not stay at home; during the nighttime, they all stay home. The lights, electric equipment, and domestic hot water (DHW) are operated accordingly. The electric equipment includes a dishwasher, refrigerator, clothes washer and dryer, range, television, etc. Since at least one resident stays home, the HVAC system keeps on for all time.

Table 1: Summary specifications of the DOE Residential Prototype Building Models

Building type	Single-family detached house Multi-family low-rise apartment buildings
Heating system type	Electric resistance Gas furnace Oil furnace Heat pump
Foundation type	Slab Crawlspace Heated basement Unheated basement

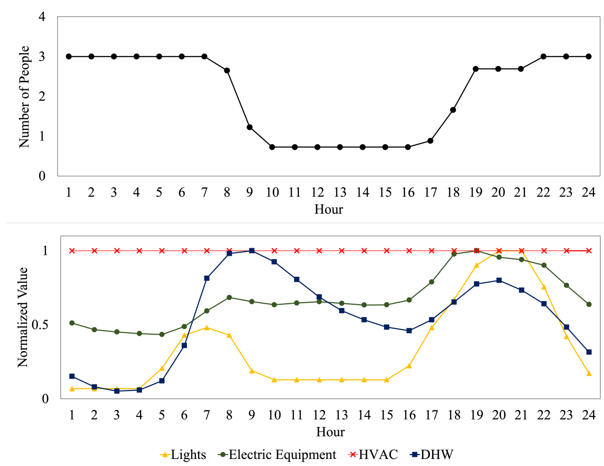

Figure 1: Current weekday schedules in a prototype residential single-family home

System Modeling

This paper proposes a novel modeling framework of optimal controls based on occupant behaviors in residential homes, supporting B2G integration research. Figure 2 shows the overall structure of an occupant-behavior-reflected modeling framework. The structure consists of the prototype model and implementation group, and each group contains unique control actions and software. The Occupancy Simulator (Chen, Hong, and Luo 2018) developed by Lawrence Berkeley National Laboratory (LBNL) provides occupancy schedules for prototype models. Other stochastic occupant schedules can also replace the occupant schedules generated by the simulator. The building prototype model includes an EnergyPlus Energy Management System (EMS) that controls the indoor environment and appliance operation status based on the given occupancy schedule and indoor environment status. The ports are prepared to connect external software for optimal control (e.g., model predictive control) and B2G integration. The following sections will describe the system modeling strategy using a simple case. The more complex case study using this modeling framework will be introduced in the planned journal article.

Assumptions

A single-family residence prototype model is chosen to introduce this modeling framework instead of a multi-family apartment building because multi-family apartments are equipped with a relatively complicated HVAC system. Appliance status, lighting, water heater, district hot water, and other human activity-related loads are designed in the prototype model. They are controlled based on their own appliance operating schedules. This framework considers the operations of these internal loads and hot water usage since they are closely related to human behaviors. The proposed framework refers to the National Renewable Energy Laboratory (NREL) Residential Hot Water Event Schedule report (Hendron, Burch, and Barker 2010) to design the internal load schedules based on occupancy. A system control logic is designed to reduce the building's energy consumption and meet the occupant's indoor environment satisfaction. Figure 3 shows the general flow of the designed system control logic. Since the purpose of this section is to introduce how to create new occupant schedules and system operations and provide the ports to connect external software, we use a simple control logic to demonstrate our effort. The system control logic consists of two parts: (1) the data gathering and simulation part and (2) the system control part. In the data gathering and simulation part, basic datasets are gathered from the software and measuring points. The prototype model runs a simulation using these datasets. In the system control part, the model-embedded system control logic determines whether the indoor environment condition satisfies the set value. The system takes future actions based on logical determination and the current status. Individual control logic by equipment and control points will be embedded in the whole framework, including the transportation. In the initial framework design, a simple temperature setpoint control logic is implemented for the case study to test the proposed framework.

Occupancy Schedules

The occupant schedule generator is a key components in this modeling framework. As shown in Figure 1, current weekday schedules embedded in the prototype models do not contain unexpected occupant behavior changes. When these models are used in occupant-related control studies, it will be a problem to represent real-world occupant schedules and provide limited occupant behavior-based system controls. It can fail to provide sufficient indoor environment satisfaction and an energy-saving effect to occupants. To overcome this problem, occupancy schedules are generated using the LBNL Occupancy Simulator and is fed as input data. The simulator gives unexpected occupancy changes to the simulated data, providing more real-world-like occupant behavior.

Since the simulator only supports the commercial building occupancy simulation currently, several assumptions are made for generating the residential building occupancy schedules. The number of occupants is set the same as in the prototype model, and in a single-family home, there is one bedroom, one kitchen, one bathroom, and a living room. The space type is designed based on the occupant's hypothetical behavior and family composition, assuming the family has one kid attending school and the parents work both. Based on this assumption, the space occupation schedules during weekdays and weekends are designed individually. Both spaces are occupied much longer and more frequently on weekends than weekdays. The occupant behaviors are also designed separately on weekdays and weekends. Since the simulator only supports the office condition, the workers' arrival and departure at the office are considered as a departure from home and arrival at home. Then, post-processing is conducted for the simulated data suitable for residential homes. The simulation considers U.S. holidays and is conducted for a year duration (1/1/2020 – 12/31/2020) of 10 minutes time step. Table 2- 4 shows the detailed occupancy simulation conditions, and Figure 4 shows the sample results of random days after the post-processing.

System Control Logic

As explained in the previous chapter, the control logic in this demonstration has a simple structure. Figure 3 shows a general system control logic embedded in the prototype model. As shown in Figure 2, LBNL Occupancy Simulator generates the occupant schedule and provides the schedule to the prototype building model as input data. The prototype model runs a simulation, and then the embedded system control logic determines

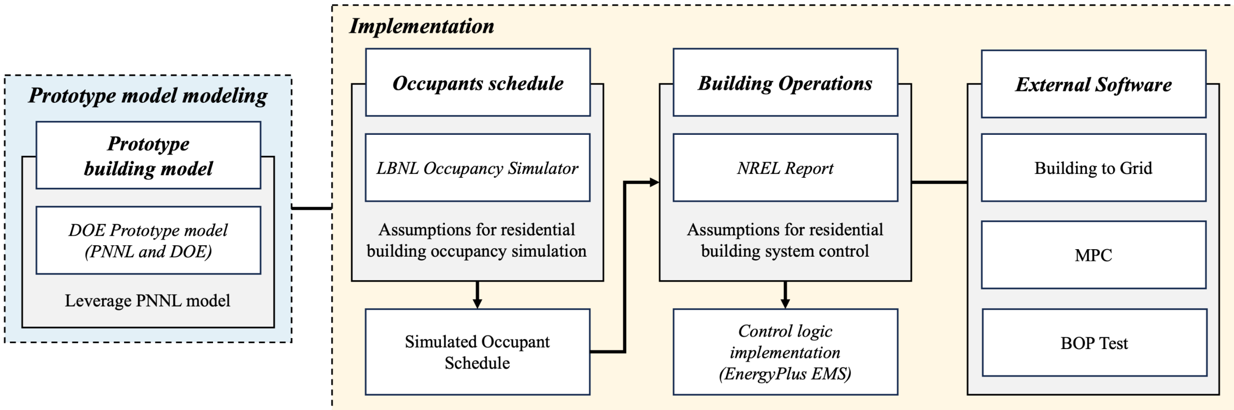

Figure 2: The overall structure of an occupant-behavior-reflected modeling framework supporting Building-to-Grid research

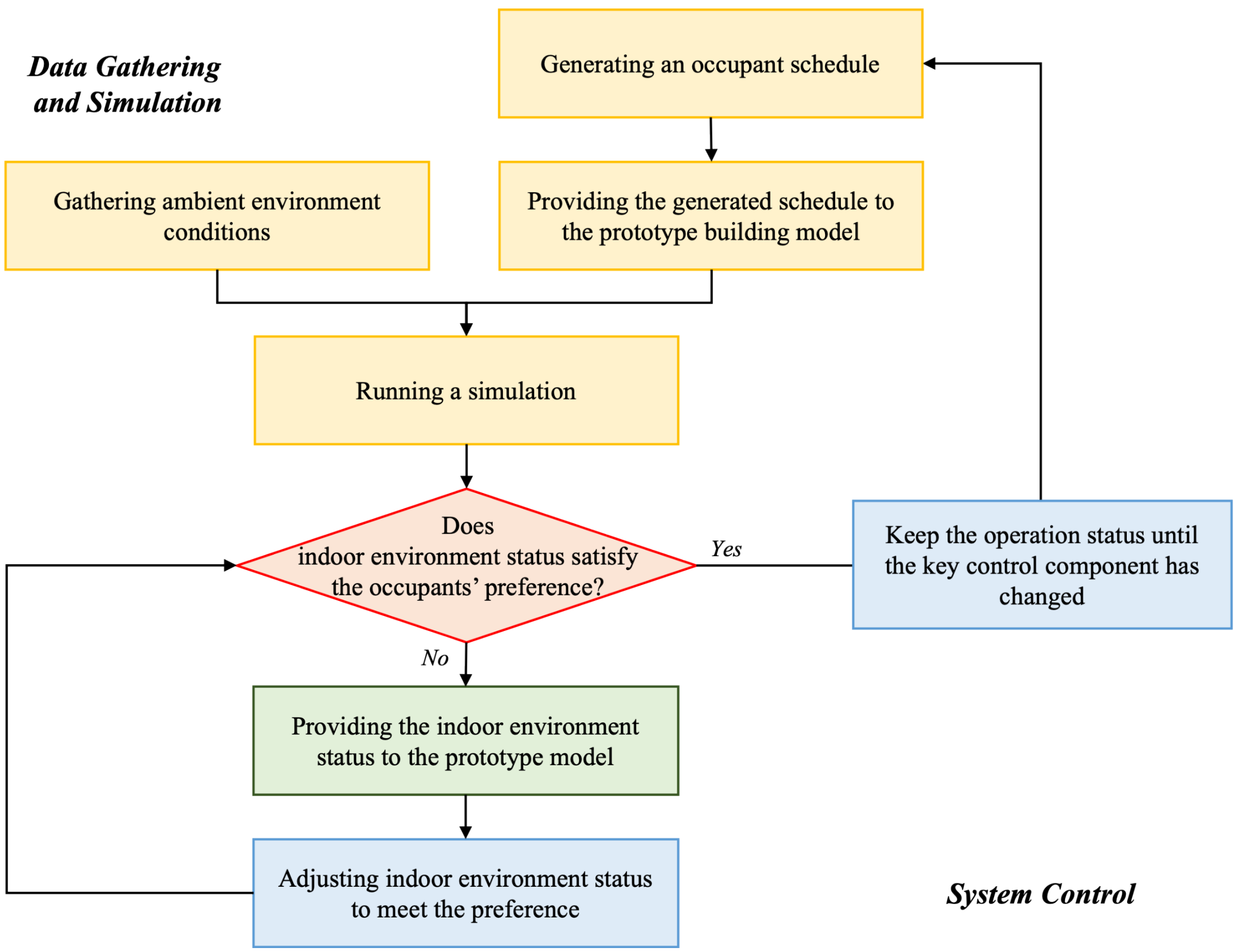

Figure 3: System control logic embedded in the prototype model

Table 2: Occupancy simulation design information: Basic simulation settings

Simulation parameters	**Simulation settings**
Building type	Office-Small
Total area	190 sqm
Number of rooms	4
Total number of occupants	3
Simulation duration	1/1/2020 - 12/31/2020
Holiday type	U.S. Holidays
Time step	10 minutes

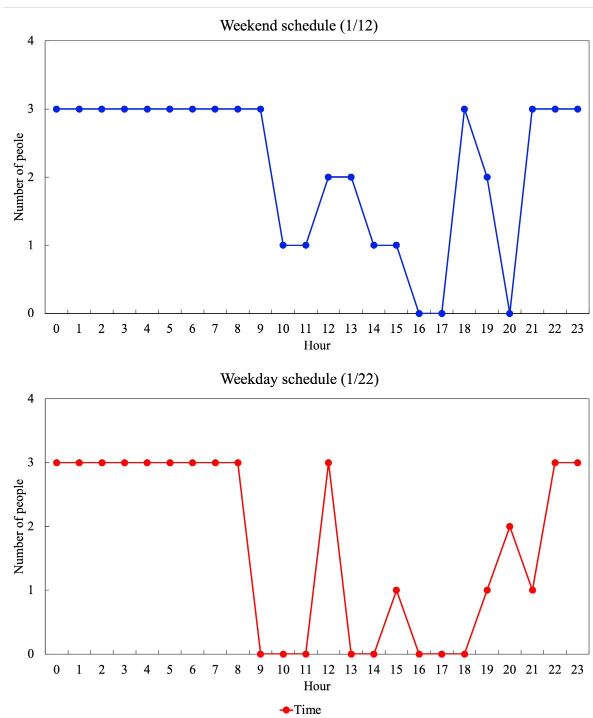

Figure 4: New occupancy schedules for a single-family home on weekdays and weekends

whether the indoor environment conditions meet the occupant's preference and takes different actions.

In the proposed framework, individual control logic and schedules for control points will be embedded in the whole model framework. The system operation logic control is performed through the Energy Management System (EMS), which is implemented in the prototype model. EMS uses EnergyPlus Runtime Language (Erl) for the programming language to program the EMS control. To model the sophisticated EMS, several assumptions for residential building system control should be made. We make relevant assumptions and build up the appliance operations by referring to the NREL Residential Hot Water Event Schedules report (Hendron, Burch, and Barker 2010). EMS controls the building system using these appliance schedules to optimize the building energy consumption and satisfy the resident's indoor environment quality preferences.

External Software Connection

Advanced optimal control strategies need to be implemented in residential homes for some studies. By leveraging the Building Optimization Testing Framework (BOPTEST) (LBNL 2023), this modeling framework provides the port to add advanced optimal control strategies, such as modeling predictive controls, into residential homes. In addition, buildings can offer to deal with the challenges of renewable energy penetration on power grids (Ye et al. 2023). Thus, building-to-grid (B2G) integration may be considered when conducting advanced optimal controls in these residential homes. This modeling framework also provides the port to conduct B2G integration by using the Hierarchical Engine for Large-scale Infrastructure Co-Simulation (HELICS) (Consortium 2022) platform to connect EnergyPlus building models and distribution-level grid models developed by the tools, such as GridLAB-D (DOE and PNNL 2023a) and OpenDSS (Xu et al. 2021). One existing example of the B2G integration research using the EnergyPlus-HELICS-GridLAB-D framework is (Waltz et al. 2023).

Case Studies

In this paper, simple case studies are conducted to demonstrate how this modeling framework works. To simplify this case, we assume there is no onsite renewable energy or electric vehicle charging station. Moreover, the case study assumes the appliance schedules have not changed to simplify the case. In other words, appliance schedules keep the original schedules already embedded in the prototype model, but the space occupancy is replaced with the simulated new schedule to show the significant effect of the occupant behavior in the residential building energy consumption. These assumptions allow us to focus on the HVAC energy consumption change according to the occupancy. The detailed appliance schedule, occupancy profile, and external software will be connected in future research. Furthermore, the system interface will be embedded in this framework. These connections enable this framework to be used for large-scale study in the future.

Table 3: Occupancy simulation design information: Space type design information

Space Type	Day of week	Number of meetings per day		Number of people per meeting		Duration of meeting (%)			
		Min.	Max.	Min.	Max.	30 min	60 min	90 min	120 min
Living Room	Weekdays	6	2	3	1	12	72	12	4
	Weekends	6	2	3	1	15	30	40	15
Kitchen	Weekdays	4	2	3	1	60	23	12	5
	Weekends	4	2	3	2	13	50	20	17

Table 4: Occupancy simulation design information: Occupant type design information

Occupant Type	Day of week	Status transition event		Short-term leaving			Average space use time percentage (%)			
		Arrival	Departure	Event name	Time	Duration (min)	Bedroom	Living room/ Kitchen	Bathroom	Outdoor
Single-family	Weekdays	8:30 AM	21:00 PM	Lunch	12:00 PM	60	70	10	5	15
				Coffee break	15:00 PM	30				
				Dinner	19:00 PM	60				
	Weekends	10:00 AM	21:00 PM	Lunch	12:00 PM	120	70	10	5	15
				Coffee break	15:00 PM	30				
				Dinner	18:00 PM	120				

The chosen prototype residential building model is a single-family residential building located in Climate Zone 4. The model has no basement and uses an electric furnace for air conditioning. To show the operation and the potential power of the framework, three cases are designed for the case study. Case 1 uses an original prototype model without any modification or implementation. Case 1 simulation result will be considered as a baseline case. A new schedule generated from the simulator is implemented in Case 2, but we do not implement EMS control logic in this case. Case 2 results will show the importance of designing the occupant behavior in detail and more realistic by comparing it to the Case 1 result. Both the new schedule and EMS control logic are implemented in Case 3, and the result will show the importance of occupant behavior-based control in the residential building and the potential power of this framework. The results of three cases are discussed regarding the annual energy consumption, annual heating and cooling energy consumption, and seasonal hourly energy consumption. The summary of the prototype model is described in Table 5, and Table 6 summarizes designed cases.

The embedded control logic for the case study controls the zone temperature setpoint. Since the original prototype model's heating and cooling temperature setpoints are designed to continuously maintain 22 °C and 24 °C respectively, the HVAC system may run during the unoccupied period to meet the temperature setpoint and cause extra energy consumption. Unlike the default control logic, new control logic is designed to adjust temperature setpoints based on the occupancy to reduce the extra energy consumption during the unoccupied period. A detailed description of new control logic is described in Table 7. If the space is unoccupied, the temperature setpoint will maintain a standby mode temperature. On the other hand, the temperature setpoint is changed to occupied mode temperature when the occupancy is detected.

Table 5: Summary of the used prototype model

Index	Specifications
Climate Zone	4A
Building type	Single-family residential house
Foundation type	Slab
HVAC system	Electric Furnace
Perimeters	1198 m
EV charging	No
Renewable energy	No

Table 6: Summary of cases

Cases	Case 1	Case 2	Case 3
Prototype Model	○	○	○
New Schedule	-	○	○
EMS Control	-	-	○

Results

Case 1: Original Model without implementations

The simulation result of Case 1 is summarized in Table 8. As shown in Table 8, the total site energy was calculated as 86.36 GJ. Site energy per total building area and the

Table 7: Implemented EMS zone heating and cooling temperature setpoint control logic

EMS Variables	HeatingSetpoint, CoolingSetpoint, ZoneAirTemperature, ZonePeople
EMS Control logic	If ZonePeople = 0 Set TemperatureSetpointHeating = 17.78 Set TemperatureSetpontCooling = 24.44 Else if ZonePeople > 0 Set TemperatureSetpointHeating = 20 Set TemperatureSetpointCooling = 22.22 End if
Actuator	TemperatureSetpointHeating, TemperatureSetpointCooling

conditioned building area are 260.72 MJ/m^2 and 391.07 MJ/m^2, respectively. The Case 1 simulation result was used as the baseline and compared to the results from the other two cases. In addition, since the software automatically sizes the equipment based on the schedule, the Case 1 HVAC sizing result was used in other models to compare the effect of each implementation in the same condition.

Table 8: Annual energy consumption of Case 1 model

	Total energy (GJ)	**Energy per total building area (MJ/m2)**	**Energy per conditioned building area (MJ/m2)**
Total site energy	86.36	260.72	391.07
Total source energy	273.49	825.69	1238.53

Case 2: New Occupant Schedule Implementation

The simulator-generated new occupant schedule was implemented in the prototype model in Case 2. As mentioned in the previous section, HVAC system sizing information identical to Case 1 was used to maintain equal conditions except for the occupant schedule. Table 9 shows the simulation result of Case 2. The total site energy was calculated as 84.46 GJ. Site energy consumption per total building area and conditioned building area were calculated as 255 MJ/m^2 and 382.49 MJ/m^2, respectively. The result shows the overall site and source energy consumption is slightly decreased compared to Case 1. It indicates that occupancy affects the building's energy consumption and shows the importance of modeling a real-life-like occupancy schedule.

Table 9: Annual energy consumption of Case 2 model

	Total energy (GJ)	**Energy per total building area (MJ/m2)**	**Energy per conditioned building area (MJ/m2)**
Total site energy	84.46	255	382.49
Total source energy	267.49	807.57	1211.35

Case 3: EMS Operation Implementation

In Case 3, EMS operation and the simulator-generated schedule were added to the model. To maintain the same simulation condition, the same occupancy schedule and modeling information used for previous cases are used for Case 3. The heating and cooling temperature setpoint control logic shown in Table 7 was programmed for the EMS operation. The simulation result is listed in the Table 10. The total site energy consumption was calculated as 73.11 GJ, which is lower energy consumption than in Case 1 and Case 2. Site energy consumption per total building area and conditioned building area also have lower energy consumption than previous cases. This result verified that embedding the occupancy-based control logic in the building system improves energy efficiency and reduces extra energy waste.

Table 10: Annual energy consumption of Case 3 model

	Total energy (GJ)	**Energy per total building area (MJ/m2)**	**Energy per conditioned building area (MJ/m2)**
Total site energy	73.11	220.73	331.09
Total source energy	231.54	699.05	1048.58

Energy Consumption in Three Cases

In this section, the energy consumption of three cases is compared regarding annual energy consumption, component energy consumption, and seasonal hourly energy consumption. As shown in Figure 5, the annual total site and source energy consumption was reduced by approximately 15% in Case 3, which has both a new schedule and EMS operation, compared to Case 1. This is because temperature setpoints are adjusted based on the occupancy in Case 3, but in Case 1, temperature setpoints are maintained the same for the whole year regardless of occupancy. Constant temperature setpoints cause extra energy consumption in Case 1.

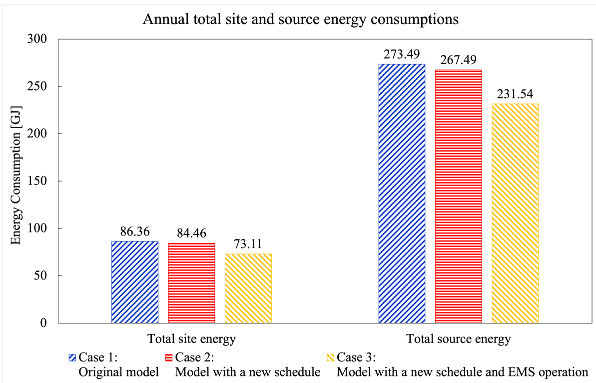

Figure 5: Annual total site and source energy consumption in three cases

Figure 6 shows the breakdown of the electricity consumption in three cases. Since the identical appliance schedules were used in three models and the EMS was programmed to control the HVAC system based on the occupancy, only heating, cooling, and fan energy are observed. As expected, heating energy consumption decreased by approximately 42%, and fan energy consumption decreased by 11% in Case 3 compared to Case 1. Interestingly, the cooling energy consumption increased by 15% in Case 3 compared to Case 1. This unexpected energy consumption results from the occupancy. The simulated occupancy data contains the noise, representing the unexpected occupancy change. In Case 2, the occupancy schedule was not directly related to the system control, and the temperature setpoints were maintained for the whole year. Thus, the cooling energy consumption decreased. However, the HVAC system was controlled by the control logic that adjusted temperature setpoints designed based on the noise-contained data in Case 3. So, the data directly affects the energy consumption calculation, and the energy consumption pattern may parallel the data.

Figure 7 and Figure 8 show the hourly building energy and fan energy consumption data on weekdays and weekends in summer and winter. A total of four days, two weekdays (1/22/2020, 7/3/2020) and two weekends (1/12/2020, 7/5/2020), in winter and summer, were chosen randomly for the comparison.

As shown in Figure 7, hourly building energy consumption shows no significant differences between the three cases. In the fan energy consumption, however, three cases show notable differences in each season and day,

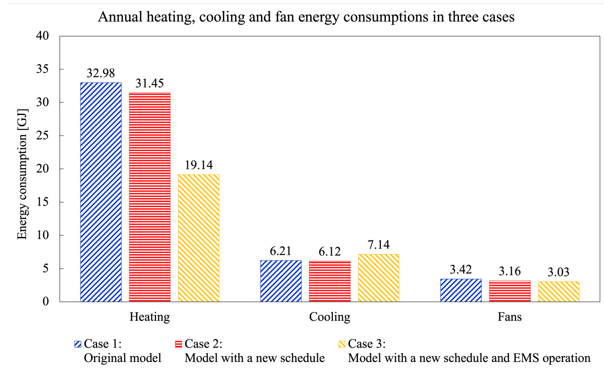

Figure 6: Annual heating, cooling and fan energy consumption in three cases

as shown in Figure 8. On weekdays, Case 1 and Case 2 have no significant differences in summer weekdays and weekends. However, Case 3 shows severe fluctuation in the fan energy consumption. This fluctuation also can be observed on weekdays in winter. Based on the analysis, this unusual energy consumption occurs when an unexpected schedule occurs. It indicates that the occupancy schedule directly influences the EMS operator implemented in Case 3. Although there is a data-mimicking issue, Case 3 consumes the lowest energy among the three cases in the winter season.

Conclusion

This paper introduced a novel modeling framework for residential homes' occupant behaviors supporting B2G integration research with case studies to demonstrate how the proposed framework works. This modeling framework is high fidelity, provides an interface to connect standardized power system tools, and has the flexibility of scaling up models and controls from a single building to many buildings. The suggested modeling framework for residential buildings emphasizes the role of occupancy schedule similar to reality and system control logic based on this realistic occupant behavior schedule. In addition, the framework operation logic provides flexibility for users to scale up the research into large-scale research. Users can customize this framework by plugging in diverse building simulation software and stochastic occupant schedules according to their needs. This novel modeling framework for residential homes demonstrates its potential for building control optimization and connection to the energy grid and its optimization. Case studies prove that reflecting real occupant behavior and related operation logic in building models is

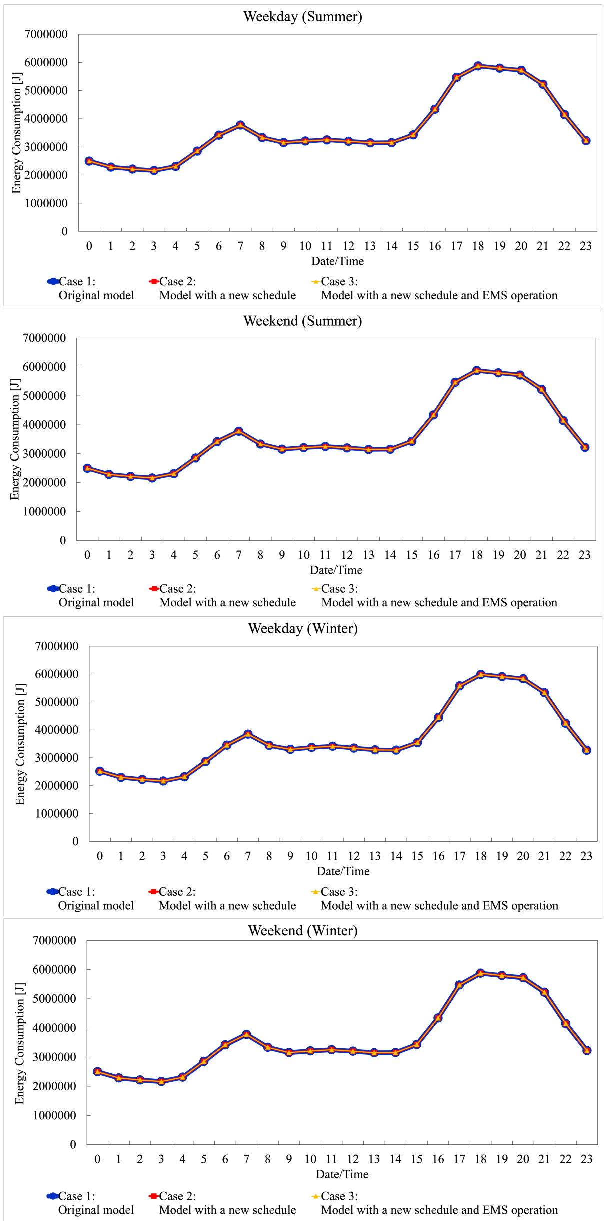

Figure 7: Hourly building energy consumption in summer and winter

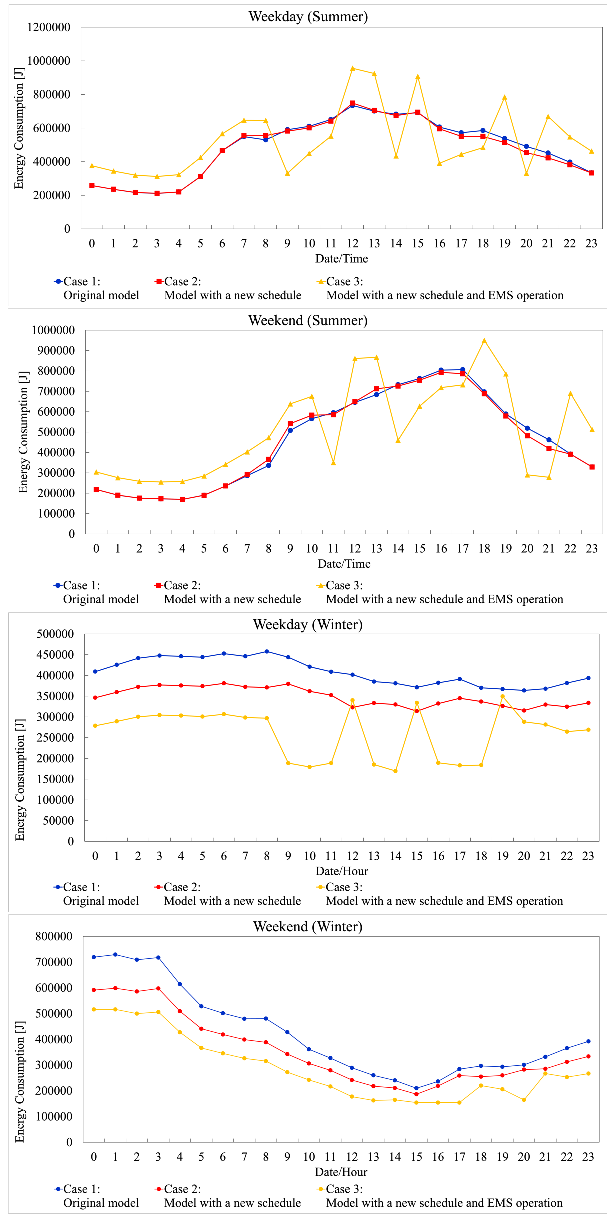

Figure 8: Hourly fan energy consumption in summer and winter

important to generate accurate simulation results. The simulation result shows that the energy consumption of the Case 3 model is significantly reduced than the other two case models. In the future, we will study more complex cases using this modeling framework and validate the framework simulation results, which will be introduced in the planned journal article.

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